Environmental sustainability assessment using dynamic Autoregressive-Distributed Lag simulations—Nexus between greenhouse gas emissions, biomass energy, food and economic growth

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HIGHLIGHTS

- This study assessed the overarching nexus between environment and economic policy.
- We employed novel dynamic simulations of Autoregressive-Distributed Lag models.
- Evidence shows a shock in food production affects long term energy consumption.
- Modernized biomass energy consumption supports the reduction of GHG emissions.
- Economic development declines energy intensity and improves energy efficiency.

GRAPHICAL ABSTRACT
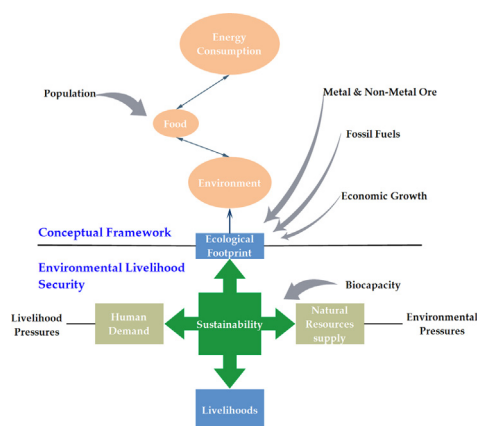
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ABSTRACT

Increasing population demand has triggered the enhancement of food production, energy consumption and economic development, however, its impact on climate change has become a global concern. This study applied a novel environmental sustainability assessment tool using dynamic Autoregressive-Distributed Lag (ARDL) simulations for model estimation of the relationships between greenhouse gas (GHG) emissions, energy, biomass, food and economic growth for Australia using data spanning from 1970 to 2017. The study found an inversed-U shaped relationship between energy consumption and income level, showing a decarbonized and services economy, hence, improved energy efficiency. While energy consumption increases emissions by 0.4 to 2.8%, biomass consumption supports Australia's transition to a decarbonized economy by reducing GHG emissions by 0.13% and shifts the demand for fossil fuel. Food and energy consumption underpin socio-economic development and vice versa. However, food waste from production and consumption increases ecological footprint, implying a lost opportunity to improve food security and reduce environmental pressure from agricultural production. There is no single path to achieving

environmental sustainability, nonetheless, the integrated approach applied in this study reveals conceptual tools which are applicable for decision making.

1. Introduction

The world population is expected to reach 9.7 billion by 2050, an increase of approximately 3 billion from today. Global wealth, especially in developing countries, has been increasing particularly in the last twenty years as a result of the industrial revolution and technological enhancement. However, the challenges for sustainable development are associated with anthropogenic induced climate change, environmental pollution and resource depletion. Countries are now trying to reduce their emission levels while at the same time improving sustainable development (United Nations, 2017).

Carbon dioxide (CO_2) is one of the primary GHG compounds, which is responsible for global warming and climate change. It is evident that over 60% of the GHG effect originates from CO_2 followed by methane which contributes around 20% (IPCC, 2014). Combustion of fossil related fuels is responsible for over 40% of the GHG emissions. It is reported that CO_2 emissions from the combustion of natural gas, coal and oil have been increasing since the industrial revolution, and it is expected to reach 40.4 Gt CO_2 in 2030 (Stanyeland, 2007).

There are several international protocols and frameworks to reduce CO_2 emissions. As a result, the Australian government has approved its commitment to reducing GHG emissions by up to 50% in the next 50 years (Commonwealth of Australia, 2016). Besides CO_2 emissions, sustainable economic development is also affected by food and energy production. Unsustainable production of food and energy can lead to exhaustion of natural resources which in turn reduces economic growth by aggravating ecosystem degradation without increasing either energy or food security (Biggs et al., 2015).

Society plays a pivotal role in the complex and meta-coupled global change system through the demand for water, food and energy (Bieber et al., 2018; Narayan and Smyth, 2005; Sarkodie and Strezov, 2018a). Thus, a surge in the growth of societies drives the tradeoff between resources in the form of coal, natural gas, hydro-energy, food and oil, which accelerates the global climate change. A "nexus" is a sustainability-driven concept that explicitly integrates the resource domains (i.e. biomass, food, energy, and among others) that past policies managed in isolation (Hoff, 2011).

Biomass is one of the renewable energy sources with increased importance, as energy policy and strategies of countries are focusing significantly on renewable sources of energy for their sustainable development (Owusu and Asumadu, 2016). It is the major source of energy in many developing countries providing around 35% of their energy demand (Demirbas et al., 2009), which raises the global consumption to 13%. Most developing countries directly use biomass as firewood for cooking and heating purposes. Major sources of biomass are wastes derived from the forest, agriculture and municipal origin with an annual global capacity of more than 13 billion metric tonnes (Müller et al., 2015) which is equivalent to 108 Gtoe, almost ten times the world's current energy demand (Weldekidan et al., 2018). Wood waste contributes to the majority of biomass energy, reaching up to 64% while municipal and agricultural wastes constitute 24% and 5%, respectively (Demirbaş, 2001).

Biomass is a CO_2 neutral source of energy, hence efficient utilization of this source through the adoption of improved conversion technologies to biofuels can bring sustainable economic development. Biofuel is a useful energy carrier obtained from biomass resources, such as forest and agricultural residues, municipal waste and energy crops, and can be used as heating, electricity and transportation fuels. Biofuels that can replace fossil fuels and petrochemicals can be produced from biomass through thermochemical, biochemical or physicochemical processes. Producing biofuels in a sustainable way can mitigate GHG emissions and offer an alternative solution to a number of environmental problems. For example, biofuels can be used as transportation fuels in vehicles and reduce CO_2 emissions by 19% and CO by 70% (Demirbas et al., 2009). Studies indicate that there are currently over a billion vehicles around the world. This number is expected to double by 2050, resulting in a higher amount of GHG emissions to the environment (Zahedi et al., 2019). The application of biofuels for transportation purposes alone can reduce a significant amount of CO_2 emissions.

Biomass energy development in Australia has been suggested as a potential cost-effective option for environmental improvements, such as soil salinity, water quality, soil protection and other benefits (Schuck et al., 2004). Only a handful of studies connect biomass energy consumption and economic growth, even though over 70% of the populace depends exclusively on biomass energy (Martins, 2018). A recent review study underpins two distinct strands of analysis (Endo et al., 2017): first, studies highlighting the strength of the interdependencies of water, food and energy under a given economic development scenario; second, those that report the cause of the intensified dependencies. Feng et al. (2016) conceptualized the latter and found a nonlinear relationship between biomass energy and population dynamics of the coupled system. Bildirici (2016) and Bildirici and Özaksoy (2018) found a short-run causal link country-level biomass energy consumption and economic growth, confirming the conservation hypothesis for Australia, Belgium, Finland and Japan, and the feedback hypothesis for the UK, France and the US. Sustainable growth is threatened due to the significant feedback effects of biomass use, gross domestic product and emissions within the West African sub-region (Adewuyi and Awodumi, 2017).

Food production system, CO_2 emissions, and economic growth have not been left out in this study. According to the IPCC report, agriculture, forestry and land use are the second contributors to anthropogenic GHG emissions after energy production (IPCC, 2014). While food security is essential for economic development, unsustainable production, management and consumption patterns negate environmental sustainability by altering ecosystems and ecological processes (Mwampamba et al., 2018; United Nations, 2015). Poor agricultural waste management, such as crop residue burning and cereal production increase atmospheric emissions by at least 1% and 1.38% respectively, while 1% of machinery use decreases emission by 0.09% (Asumadu-Sarkodie and Owusu, 2017). It is critical to minimize the trade-offs while maximizing the synergies in the use of natural resources for food and energy production while achieving environmental sustainability. Sustainable development policies can be achieved through the analysis of the combined impacts of the sub-sectors under policy uncertainties.

Despite a growing body of literature, the "nexus" concept remains unclear from econometrics perspective. Studies have informed numerous policies by linking economic growth, resource demand, and emissions (as a proxy for environmental degradation), which may lead to erroneous conclusions due to the interconnectedness of resource use (Soimakallio, 2012). The importance of biomass energy development in Australia requires an explicit understanding of its impact on emissions. This study contributes to the advocacy for

integrated policy options on sustainable growth by providing a clear link between sectoral energy and food consumption, and the growth pathways in Australia, which is ignored due to model limitations and data availability.

This study adopts novel dynamic simulations of ARDL model capable of examining the effect of the counterfactual changes in regressors on the response variable, which improves the complex nature and difficulty in the interpretation of the existing ARDL model. Secondly, this study develops five conceptual tools capable of accelerating Australia's agenda towards achieving sustainable development. Finally, the study contributes to the global debate on environmental sustainability by assessing the overarching nexus between the environment and economic policy.

2. Materials and method

2.1. Data

Table 1 presents the description of thirteen data series used in the model estimation. The thirteen variables spanning between 1970 and 2017 include food production index, energy use, CO_2 emissions, total greenhouse gas emissions, GDP, GDP per capita, adjusted savings: natural resources depletion, biomass extraction, fossil fuels extraction, metal ores extraction, non-metallic minerals extraction, biocapacity, and ecological footprint. The selection of the data series is based on the United Nations' indicators for sustainable development (DiSano, 2002). To examine the characteristics of the variables, the study examines the descriptive statistical analysis presented in Table 2. Prior to the model estimation, a logarithmic transformation was applied to give the data series a constant variance.

The ARDL model with dynamic simulations proposed by Jordan and Philips (2018) follows the standard pathway expressed as:

$$\Delta(y)_t = \alpha_0 + \theta_0(y)_{t-1} + \theta_1(x_1)_{t-1} + \ldots + \theta_k(x_k)_{t-1} \\ + \sum_{i=1}^{p} \alpha_i \Delta(y)_{t-1} + \sum_{j=0}^{q_1} \beta_{1j} \Delta(x_1)_{t-j} + \ldots \\ + \sum_{j=0}^{q_k} \beta_{kj} \Delta(x_k)_{t-j} + \varepsilon_t \tag{1}$$

where a change in the dependent variable (y) is a function of the intercept (α_0), all the independent variables at $t-1$ in levels to a maximum of p and q_k lags in their first-differences (Δ) with error term (ε) in time t. The ARDL bounds testing procedure for a level relationship by Pesaran et al. (2001) is examined using Kripfganz and Schneider (2018) critical values and approximate p-values based on response surface regressions. To reject the null hypothesis of no level relationship $[H_0 = \theta_0 + \theta_1 + \ldots + \theta_k = 0]$, the F-statistic from the jointly zero estimation of all parameters on the independent variables in level and the lagged

dependent variable coefficient must be above the upper bound critical values $[I(1)]$, coupled with statistically significant approximate p-values.

Based on the empirical specification expressed in Eq. (1), the error correction forms of the 7 ARDL-bounds models are estimated as:

MODEL 1:

$$\Delta \ln(ENERGY)_t = \alpha_0 + \theta_0 \ln(ENERGY)_{t-1} + \beta_1 \Delta \ln(FOOD)_t \\ + \theta_1 \ln(FOOD)_{t-1} + \beta_2 \Delta \ln(NATRES)_t \\ + \theta_2 \ln(NATRES)_{t-1} + \beta_3 \Delta \ln(CO_2E)_t \\ + \theta_3 \ln(CO_2E)_{t-1} + \beta_4 \Delta \ln(PCGDP)_t \\ + \theta_4 \ln(PCGDP)_{t-1} + \beta_5 \ln\left(PCGDP^2\right)_t \\ + \theta_5 \ln\left(PCGDP^2\right)_{t-1} \tag{2}$$

MODEL 2:

$$\Delta \ln(GHG)_t = \alpha_0 + \theta_0 \ln(GHG)_{t-1} + \beta_1 \Delta \ln(BIOMAS)_t \\ + \theta_1 \ln(BIOMAS)_{t-1} + \beta_2 \Delta \ln(FOSSIL)_t \\ + \theta_2 \ln(FOSSIL)_{t-1} + \beta_3 \Delta \ln(MORES)_t \\ + \theta_3 \ln(MORES)_{t-1} + \beta_4 \Delta \ln(NMMIN)_t \\ + \theta_4 \ln(NMMIN)_{t-1} + \beta_5 \ln(GDP)_t \\ + \theta_5 \ln(GDP)_{t-1} \tag{3}$$

MODEL 3:

$$\Delta \ln(GHG)_t = \alpha_0 + \theta_0 \ln(GHG)_{t-1} + \beta_1 \Delta \ln(ENERGY)_t \\ + \theta_1 \ln(ENERGY)_{t-1} + \beta_2 \Delta \ln(NATRES)_t \\ + \theta_2 \ln(NATRES)_{t-1} + \beta_3 \Delta \ln(BCAPA)_t \\ + \theta_3 \ln(BCAPA)_{t-1} + \beta_4 \Delta \ln(EFCONS)_t \\ + \theta_4 \ln(EFCONS)_{t-1} + \beta_5 \Delta \ln(GDP)_t \\ + \theta_5 \ln(GDP)_{t-1} \tag{4}$$

MODEL 4:

$$\Delta \ln(CO_2E)_t = \alpha_0 + \theta_0 \ln(CO_2E)_{t-1} + \beta_1 \Delta \ln(ENERGY)_t \\ + \theta_1 \ln(ENERGY)_{t-1} + \beta_2 \Delta \ln(NATRES)_t \\ + \theta_2 \ln(NATRES)_{t-1} + \beta_3 \Delta \ln(GDP)_t \\ + \theta_3 \ln(GDP)_{t-1} \tag{5}$$

Table 1
Description of data series.

Abbreviation	Series description	Unit	Source
FOOD	Food production index	Index, 2004–2006 = 100	World Bank (2018)
ENERGY	Energy use	kg of oil equivalent per capita	World Bank (2018)
CO_2E	CO_2 emissions	kt	World Bank (2018)
GHG	Total greenhouse gas emissions	kt of CO_2 equivalent	World Bank (2018)
GDP	GDP	Current US$	World Bank (2018)
PCGDP	GDP per capita	Current US$	World Bank (2018)
NATRES	Adjusted savings: natural resources depletion	% of GNI	World Bank (2018)
BIOMAS	Biomass	tons	Materials Flow (2017)
FOSSIL	Fossil fuels	tons	Materials Flow (2017)
MORES	Metal ores	tons	Materials Flow (2017)
NMMIN	Non-metallic minerals	tons	Materials Flow (2017)
BCAPA	Biocapacity	gha	Global Footprint Network (2017)
EFCONS	Ecological footprint	gha	Global Footprint Network (2017)

Table 2
Descriptive statistics.

Statistic	BCAPA	BIOMAS	CO$_2$E	EFCONS	ENERGY	FOOD	FOSSIL	GDP	GHG	MORES	NATRES	NMMIN	PCGDP
Mean	3.18E+08	1.78E+08	277,716.7	1.43E+08	5066.54	79.93915	2.98E+08	4.99E+11	638,003.2	4.53E+08	1.8355	1.69E+08	24,514.29
Median	3.17E+08	1.68E+08	277,397.5	1.36E+08	5075.649	74.63	2.71E+08	3.25E+11	482,298.3	3.77E+08	1.7148	1.71E+08	18,697.01
Maximum	3.37E+08	2.34E+08	394,792.9	1.98E+08	5964.666	109.72	5.98E+08	1.57E+12	1,241,516	1.24E+09	4.1945	2.37E+08	67,990.29
Minimum	2.93E+08	1.10E+08	147,618.8	1.01E+08	3989.63	50.67	78,873,820	4.13E+10	314,446.1	99,932,549	0.4616	1.05E+08	3299.037
Std. Dev.	10,047,698	40,835,205	75,158.48	2.76E+07	553.5617	18.8317	1.55E+08	4.59E+11	302,683.1	3.15E+08	0.9605	3.33E+07	18,785.92
Skewness	−0.0301	0.0199	−0.0566	0.4509	−0.2159	0.1521	0.3005	1.1245	0.7132	1.0121	0.7044	−0.1882	1.0104
Kurtosis	2.6772	1.4855	1.8519	1.9837	1.9058	1.5451	1.8888	2.9242	1.8849	3.1696	2.6561	2.2265	2.7995
Jarque-Bera	0.2022	4.5904	2.4957	3.4613	2.6522	4.3266	3.1921	10.1267	5.8737	8.2518	4.1180	1.4799	8.2473
Probability	0.9039	0.1007	0.2871	0.1772	0.2655	0.1149	0.2027	0.0063***	0.0530**	0.0161**	0.1276	0.4771	0.0162**
Observations	45	48	45	45	46	47	48	48	43	48	47	48	48

***, ** denote significance at 1, and 5% level.

MODEL 5:

$$\Delta \ln(FOOD)_t = \alpha_0 + \theta_0 \ln(FOOD)_{t-1} + \beta_1 \Delta \ln(ENERGY)_t$$
$$+ \theta_1 \ln(ENERGY)_{t-1} + \beta_2 \Delta \ln(GHG)_t$$
$$+ \theta_2 \ln(GHG)_{t-1} + \beta_3 \Delta \ln(EFCONS)_t$$
$$+ \theta_3 \ln(EFCONS)_{t-1} + \beta_4 \Delta \ln(GDP)_t$$
$$+ \theta_4 \ln(GDP)_{t-1} \qquad (6)$$

MODEL 6:

$$\Delta \ln(EFCONS)_t = \alpha_0 + \theta_0 \ln(EFCONS)_{t-1} + \beta_1 \Delta \ln(BIOMAS)_t$$
$$+ \theta_1 \ln(BIOMAS)_{t-1} + \beta_2 \Delta \ln(FOSSIL)_t$$
$$+ \theta_2 \ln(FOSSIL)_{t-1} + \beta_3 \Delta \ln(MORES)_t$$
$$+ \theta_3 \ln(MORES)_{t-1} + \beta_4 \Delta \ln(NMMIN)_t$$
$$+ \theta_4 \ln(NMMIN)_{t-1} + \beta_5 \Delta \ln(GDP)_t$$
$$+ \theta_5 \ln(GDP)_{t-1} + \beta_6 \Delta \ln(FOOD)_t$$
$$+ \theta_6 \ln(FOOD)_{t-1} \qquad (7)$$

MODEL 7:

$$\Delta \ln(BCAPA)_t = \alpha_0 + \theta_0 \ln(BCAPA)_{t-1} + \beta_1 \Delta \ln(ENERGY)_t$$
$$+ \theta_1 \ln(ENERGY)_{t-1} + \beta_2 \Delta \ln(NATRES)_t$$
$$+ \theta_2 \ln(NATRES)_{t-1} + \beta_3 \Delta \ln(GDP)_t$$
$$+ \theta_3 \ln(GDP)_{t-1} \qquad (8)$$

3. Results and discussion

3.1. Unit root

The initial step of testing the level relationships between the dependent variables and their regressors is to ensure that the data series, especially the dependent variables are integrated of order one, I(1). Second, all the regressors must not be integrated of order one or exhibit seasonal unit roots. To meet the requirement, the study employed three unit root tests such as Phillip-Perron (PPERRON), Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) to examine the order of integration of the variables. Table 3 presents the results of PPERRON, ADF and KPSS unit root tests. While PPERRON and ADF are tested under the null hypothesis of a unit root, KPSS, on the other hand, has a null hypothesis of stationarity. Evidence from Table 3 reveals that at 1% significance level, the null hypothesis of a unit root (PPERRON and ADF) or stationarity (KPSS) cannot be rejected at level in almost all the variables, however, rejected at first-difference. Hence, all the data series are integrated of order one and potential candidates for ARDL bounds cointegration.

3.2. Cointegration

After meeting the pre-requirements, the next step is to examine the level relationships exhibited by the proposed models. The data series are said to be integrated of order one if the current state of the variables is a function of all past stochastic shocks plus to some extent, new innovations. While short-run perturbations may cause disequilibrium of the series, this disequilibrium is corrected over time as the series moves backwards to a stable long-run relationship (Jordan and Philips,

Table 3
Unit root tests.

Data series	KPSS		ADF		PPERRON	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
BIOMAS	0.2550	0.0220***	−1.5530	−11.4170***	−1.3020	−11.8700***
FOSSIL	0.8160	0.0199***	1.6980	−7.8730***	2.6130	−7.9080***
MORES	0.8600	0.1930***	5.0650	−3.5520***	4.4250	−3.4940***
NMMIN	0.1740	0.0189***	−1.6860	−10.5510***	−1.5370	−10.7620***
BCAPA	0.2970	0.0172***	−4.0850***	−10.4860***	−4.1170***	−11.9430***
EFCONS	0.4760	0.0607***	−1.6020	−7.5880***	−1.4950	−7.7580***
FOOD	0.2170	0.0246***	−1.2440	−10.0850***	−1.0110	−10.6450***
ENERGY	0.3580	0.0620***	−1.7130	−6.9940***	−1.7290	−6.9840***
CO$_2$E	0.1320	0.0992***	−1.6190	−5.8200***	−1.5730	−5.8620***
GHG	0.3380	0.0764***	−1.4930	−9.7290***	−1.4210	−9.1500***
GDP	0.8800	0.0834***	0.4240	−4.8010***	0.1340	−4.7780***
PCGDP	0.7470	0.0861***	−0.1760	−4.9980***	−0.3740	−4.9680***
NATRES	0.3960	0.0551***	−2.5210	−7.3270***	−2.4650	−7.4440***

*** Denotes the rejection of the null hypothesis of unit root at 1% significance level.

Table 4
ARDL bounds cointegration test.

Models		Statistic	10%		5%		1%		p-Value	
			I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
lnGHG = f (lnBIOMAS lnFOSSIL lnMORES lnNMMIN lnGDP)	F	11.29	2.44	3.88	2.98	4.64	4.30	6.49	0.0000	0.0000
lnFOOD = f (lnENERGY lnGDP lnGHG lnEFCONS)	F	6.92	2.64	3.91	3.21	4.64	4.56	6.39	0.0010	0.0060
lnCO₂E = f (lnENERGY lnGDP lnNATRES)	F	10.63	2.83	4.12	3.47	4.95	5.01	6.91	0.0000	0.0010
lnGHG = f (lnENERGY lnGDP lnNATRES lnBCAPA lnEFCONS)	F	6.64	2.47	3.80	2.99	4.50	4.25	6.19	0.0010	0.0070
lnEFCONS = f (lnBIOMAS lnFOSSIL lnMORES lnNMMIN lnFOOD lnGDP)	F	5.25	2.35	3.65	2.82	4.29	3.94	5.80	0.0020	0.0180
lnENERGY = f (lnFOOD lnNATRES lnCO₂E lnPCGDP lnPCGDP²)	F	10.34	2.44	3.80	2.96	4.50	4.19	6.18	0.0000	0.0000
lnBCAPA = f (lnNATRES lnGDP lnENERGY)	F	9.26	2.88	4.05	3.51	4.83	4.99	6.64	0.0000	0.0010

NB: The null hypothesis of no level relationship is rejected when the F-statistic is above the 10%, 5% and 1% upper bound critical values, corroborated by the p-value.

2018). Such series exhibits a cointegrating relationship. However, since not all relationships between I(1) data series appear to validate the presence of cointegration, it becomes essential to test the validity of a cointegrating relationship. Table 4 presents the results of the ARDL bounds cointegration test using response surface regression with accurate critical values and approximate p-values proposed by Kripfganz and Schneider (2018). The ARDL bounds cointegration test reveals that the F-statistic values of all variables in level and the lagged dependent variable coefficient in the estimated models are above the upper bound critical values [I(1)], corroborated by statistically significant approximate p-values. Thus, validating the cointegrating relationships between I(1) variables in all the 7 estimated models.

3.3. Dynamic stimulated ARDL models

Contrary to the complexities of existing ARDL models in examining the effect of short- and long-run in complex model specifications, Jordan and Philips (2018) introduced a novel dynamic stimulated ARDL model capable of estimating, stimulating and automatically plotting predictions of counterfactual change in one regressor on the dependent variable while holding other regressors constant. To apply the dynamic stimulated ARDL technique, the data series for the model estimation should be integrated of order one and cointegrated, for which the variables in this work meet the requirements. The dynamic ARDL error correction algorithm utilized for the 7 models adopts 5000 simulations of the vector of parameters from a multivariate normal distribution. Table 5 presents the results of the dynamic stimulated ARDL error correction models.

The study further examined the effect of counterfactual change in regressors on the dependent variables using graphical representations depicted in Figs. 1–8. Sustainable livelihoods play a critical role in achieving the sustainable development goals outlined by the United Nations. This study presents the different forms of interaction that reveal the various determinants of sustainable livelihoods.

3.3.1. Energy-food-emission-income level nexus

Table 5 column 2 reveals a negative and statistically significant error correction of −0.24—representing 24% speed of correcting the previous disequilibrium over time as the variables move backwards to a stable long-run relationship. The coefficient on food is positive in the long-run and negative in the short-run, but insignificant to make statistical inferences. Though the nexus between energy and food is a conceptual tool critical for achieving sustainable development (Biggs et al., 2015), yet this study provides statistically insignificant results to support previous studies. The study found a positive short-run relationship between energy consumption and CO₂ emissions but insignificant negative relationship in the long-run. The results are in line with Bekun et al. (2019b); Sarkodie and Adom (2018) for South Africa and Kenya. The short-term effect of CO₂ emissions spurs energy consumption for cooling and heating purposes due to the abnormal change in the global average temperatures. Climate change and socio-economic development were found to increase the intensity of energy-food nexus in

South Africa (Conway et al., 2015). An increase in natural resources depletion, which comprises of forest, energy and mineral depletion is found to significantly decline energy consumption in the long-run but insignificant in the short-run. Increasing levels of natural resources depletion affect environmental livelihood security due to an imbalance between natural resource supply and human demand. Hence, environmental livelihood insecurity affects energy security, leads to livelihood pressures and hampers sustainability. Growth in income level is observed to have a positive effect on energy consumption in the long-run. To examine the role of income level on energy efficiency, the study included the square of income level in the model. While the coefficient of income level is positive, the square of income level is found to have a significant negative coefficient, signifying an inversed-U shaped relationship. While growth in income level intensifies energy consumption (growth hypothesis), intensive energy utilization declines after reaching a turning point of income level, hence, translating into energy efficiency due to a decline in energy intensity. The results are in line with Rajbhandari and Zhang (2018) for 56 countries. They found a negative effect of income on energy intensity in the lower, middle- and higher-income countries. Thus, growth in income levels in Australia triggers energy efficiency—sustainable utilization of energy and its related services. Fig. 1 depicts the impulse-response plot of food-energy nexus and income-energy nexus. Fig. 1(a) shows that a +1 shock at 10th scenario time appears negative in the short-run but increases eventually and turns positive with over 1 predicted value in the long-run. Contrary, −1 shock produces a positive effect in the short-run but turns negative and declines over time in the long-run. Food production, such as residues of crops and livestock are a great source of biomass energy generation (biofuels, biopower, and traditional fuels like charcoal and wood fuel). Hence, a shock in food production affects long term energy consumption. While a positive shock in income levels intensifies energy access and utilization, a negative shock affects energy access and consumption, meaning that energy security is dependent on income.

3.3.2. Climate change-natural resource-biomass-economic growth nexus

Model 2 (Table 5 column 3), model 3 (Table 5 column 4) and model 4 (Table 5 column 6) show ~56%|~58%|~24% speed of adjusting past disequilibrium in emissions to equilibrium following a stable long-run relationship. The coefficient on lnGDP in Model 2–3 is negative and statistically significant in both short- and long-run. The empirical evidence signifies a negative relationship between GHG emissions and economic development in both short-term and long-term. Thus, the increasing levels of Australia's dominant services economy promotes environmental sustainability. In line with a similar result in the US (Bilgili, 2012), a long-run negative relationship is observed between GHG emissions and biomass energy consumption. The possible explanation is the sustainable management of biomass fuel sources for the full life cycle, which ensures the re-absorption of produced CO₂ emissions to the feedstock supply chain. Australia's lignocellulose supply comes from agricultural residues, organic municipal and agro-industrial waste, wastewater, wood waste and animal residues

Table 5
Results of dynamic stimulated ARDL models.

| Variable	$\Delta lnENERGY_t$ (Model 1)	$\Delta lnGHG_t$ (Model 2)	$\Delta lnGHG_t$ (Model 3)	$\Delta lnCO_2E_t$ (Model 4)	$\Delta lnFOOD_t$ (Model 5)	$\Delta lnEFCONS_t$ (Model 6)	$\Delta lnBCAPA_t$ (Model 7)
$\Delta lnENERGY_t$			1.2385 (0.8757)	0.8978*** (0.1594)	−0.0286 (0.5062)		−0.1816 (0.1937)
$lnENERGY_{t-1}$	−0.2389[a]*** (0.1160)		2.8212*** (0.9910)	0.3580** (0.1383)	0.4560 (0.4973)		0.2069 (0.1432)
$\Delta lnGHG_{t-1}$					0.1176 (0.0813)		
$lnGHG_{t-1}$		−0.5630[a]*** (0.1075)	−0.5751[a]*** (0.1354)		−0.0260 (0.0637)		
$\Delta lnFOOD_t$	−0.0489 (0.0459)					0.8143*** (0.2698)	
$lnFOOD_{t-1}$	0.0270 (0.0459)				−0.4565[a]*** (0.1545)	0.6607* (0.3675)	
$\Delta lnBIOMAS_t$		0.0016 (0.2220)				−0.0038 (0.1688)	
$lnBIOMAS_{t-1}$		−0.1329*** (0.2548)				−0.4114 (0.3046)	
$\Delta lnNATRES_t$	0.0068 (0.0097)		−0.1214* (0.0685)	−0.0172 (0.0123)			−0.0074 (0.0153)
$lnNATRES_{t-1}$	−0.0133* (0.0076)		−0.0983** (0.0480)	0.0012 (0.0083)			−0.0293*** (0.0106)
$\Delta lnFOSSIL_t$		−0.1329 (0.4768)				−0.0203 (0.2832)	
$lnFOSSIL_{t-1}$		−0.3142 (0.2452)				−0.0677 (0.1512)	
$\Delta lnCO_2E_t$	0.5021*** (0.0957)						
$lnCO_2E_{t-1}$	−0.0191 (0.0697)			−0.2351[a]*** (0.0883)			
$\Delta lnBCAPA_t$			0.7719 (0.8111)				
$lnBCAPA_{t-1}$			1.4499* (0.8427)				−0.8750[a]*** (0.1642)
$\Delta lnGDP_t$		−0.3977* (0.2050)	−0.0965 (0.2376)	0.0352 (0.0400)	−0.2279* (0.1187)	0.3481*** (0.1177)	−0.0629 (0.0479)
$lnGDP_{t-1}$		−0.2325* (0.1182)	−0.2259** (0.1019)	0.0243 (0.0199)	0.0451 (0.0454)	−0.0785 (0.0613)	−0.0279 (0.0192)
$\Delta lnPCGDP_t$	0.0828 (0.3821)						
$lnPCGDP_{t-1}$	0.2420** (0.1023)						
$\Delta lnPCGDP_t^2$	−0.0015 (0.0192)						
$lnPCGDP_{t-1}^2$	−0.0105** (0.0048)						
$\Delta lnEFCONS_t$			−0.1016 (0.3713)		0.5149*** (0.1506)		
$lnEFCONS_{t-1}$			0.7304** (0.2967)		0.1524 (0.1356)	−0.3611[a]*** (0.1248)	
$\Delta lnMORES_t$		−0.0461 (0.3356)				0.0889 (0.1956)	
$lnMORES_{t-1}$		0.4624** (0.2040)				0.0593 (0.1220)	
$\Delta lnNMMIN_t$		0.6714** (0.2872)				0.2540 (0.1813)	
$lnNMMIN_{t-1}$		0.4809 (0.3888)				0.4187* (0.2415)	
Constant	0.7993 (0.6279)	−18.3749*** (5.8324)	−52.4789*** (16.7268)	−0.7394 (0.5694)	−5.5829* (3.2705)	5.9645 (4.4392)	16.1264*** (2.9698)
N	44	42	42	42	39	44	42
Sims	5000	5000	5000	5000	5000	5000	5000
Prob > F	0.0001***	0.0002***	0.0054***	0.0000***	0.0029***	0.0021***	0.0008***
R^2	0.66	0.65	0.54	0.61	0.54	0.60	0.49
Diagnostics							
$\chi^2_{LM-ARCH}$	0.80	0.10	0.02	0.96	1.32	0.39	3.32*
χ^2_{LM-B-G}	0.79	2.08	6.78***	0.06	2.69	0.44	10.94***

***, **, * denote significance at 1, 5, and 10%; [a] denotes the speed of adjustment; parenthesis ( ) denotes the standard error; Sims represents the number of simulations; $\chi^2_{LM-ARCH}$ represents the LM test for autoregressive conditional heteroskedasticity (ARCH); and χ^2_{LM-B-G} is the Breusch-Godfrey LM test for autocorrelation.

(Bioenergy Australia, 2018). Hence, biomass energy consumption supports a transition to a decarbonized economy by reducing GHG emissions while shifting the demand for fossil fuel energy and its related products.

While no significant outcome is observed between fossil fuels and GHG emissions, other disaggregate natural resources extraction such as metal ores and non-metallic minerals have a positive impact on GHG emissions in the long-run and short-run, respectively. Visible
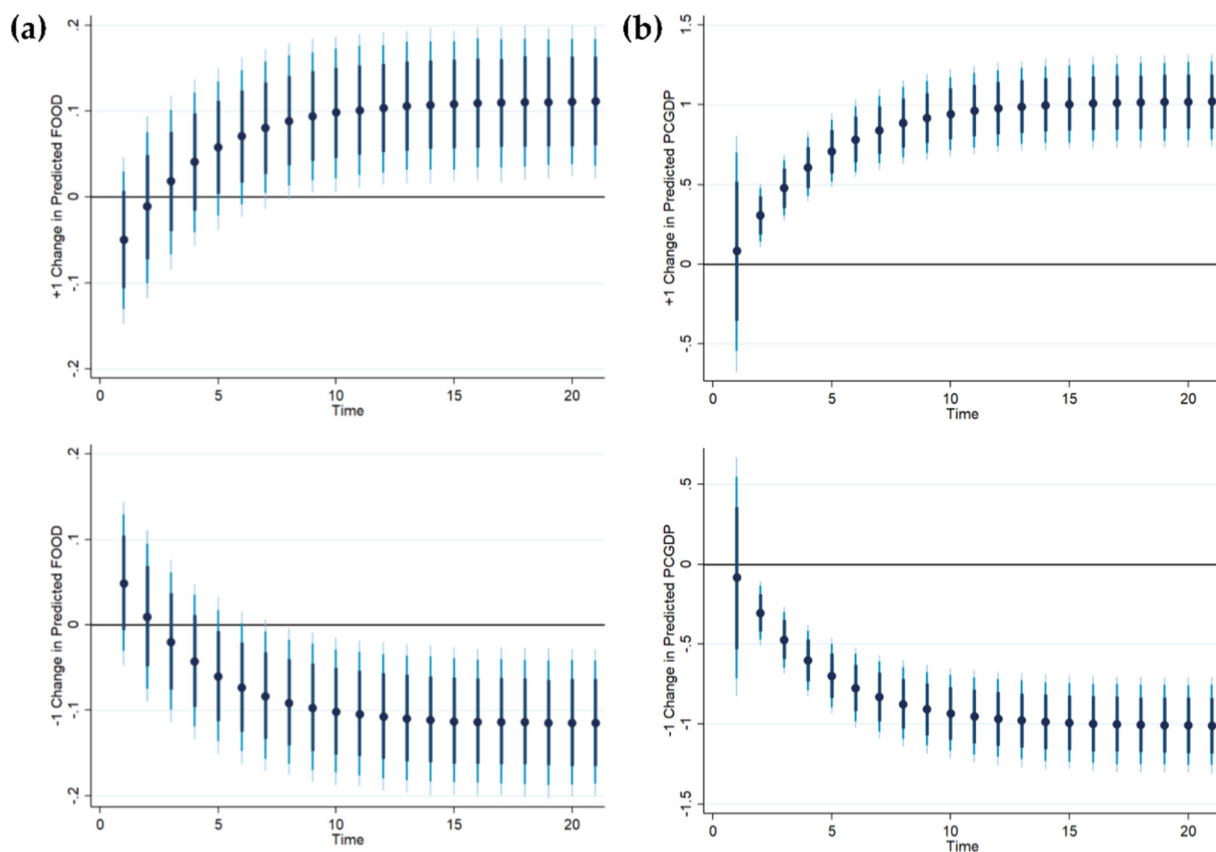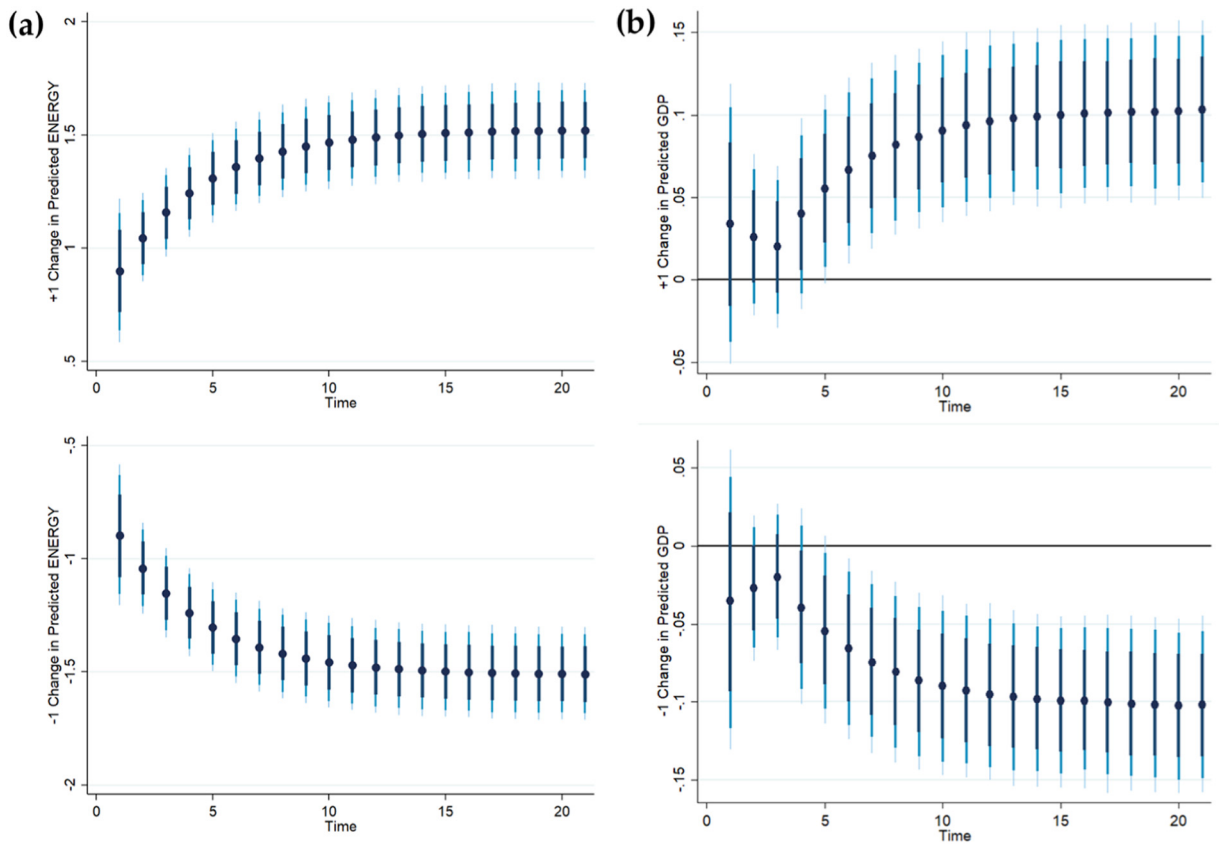
Fig. 1. (a) Model 1: change (±1%) in predicted FOOD on ENERGY (b) Model 1: change in predicted PCGDP on ENERGY. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
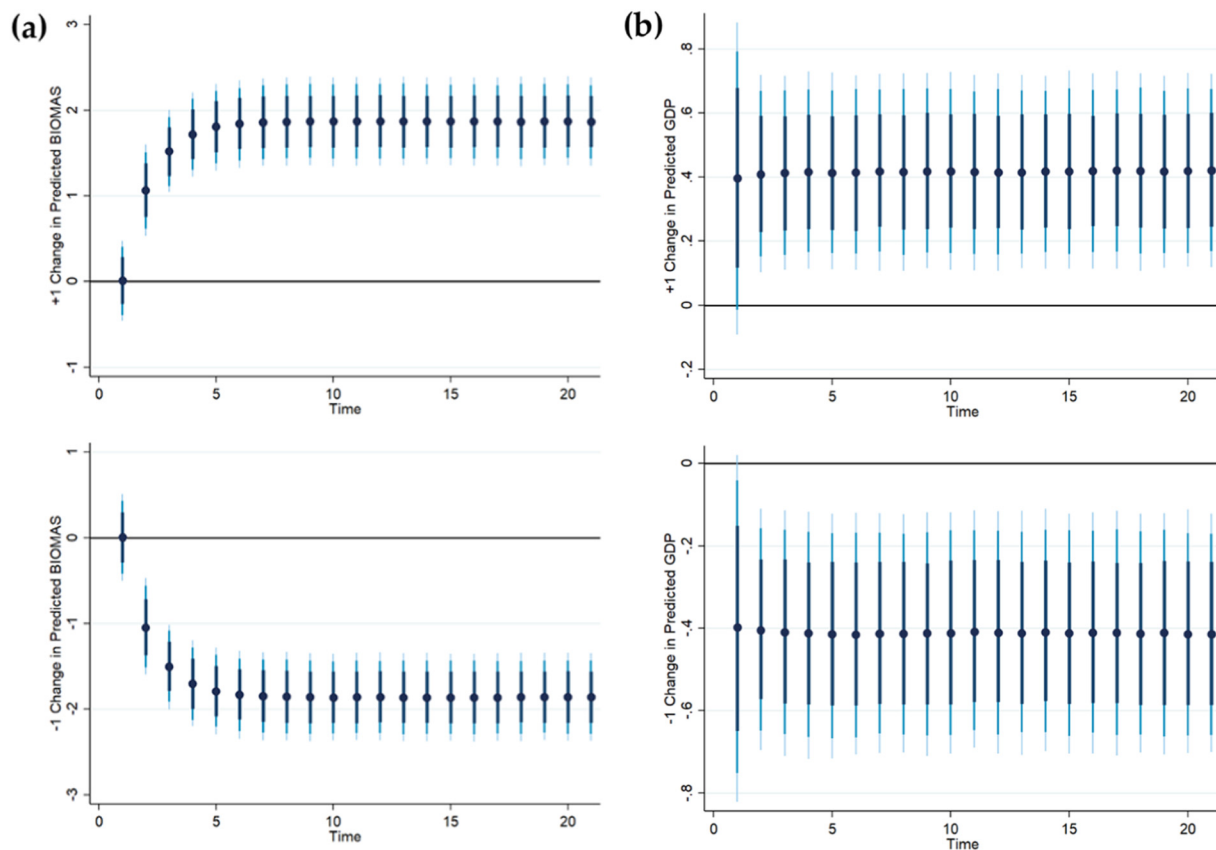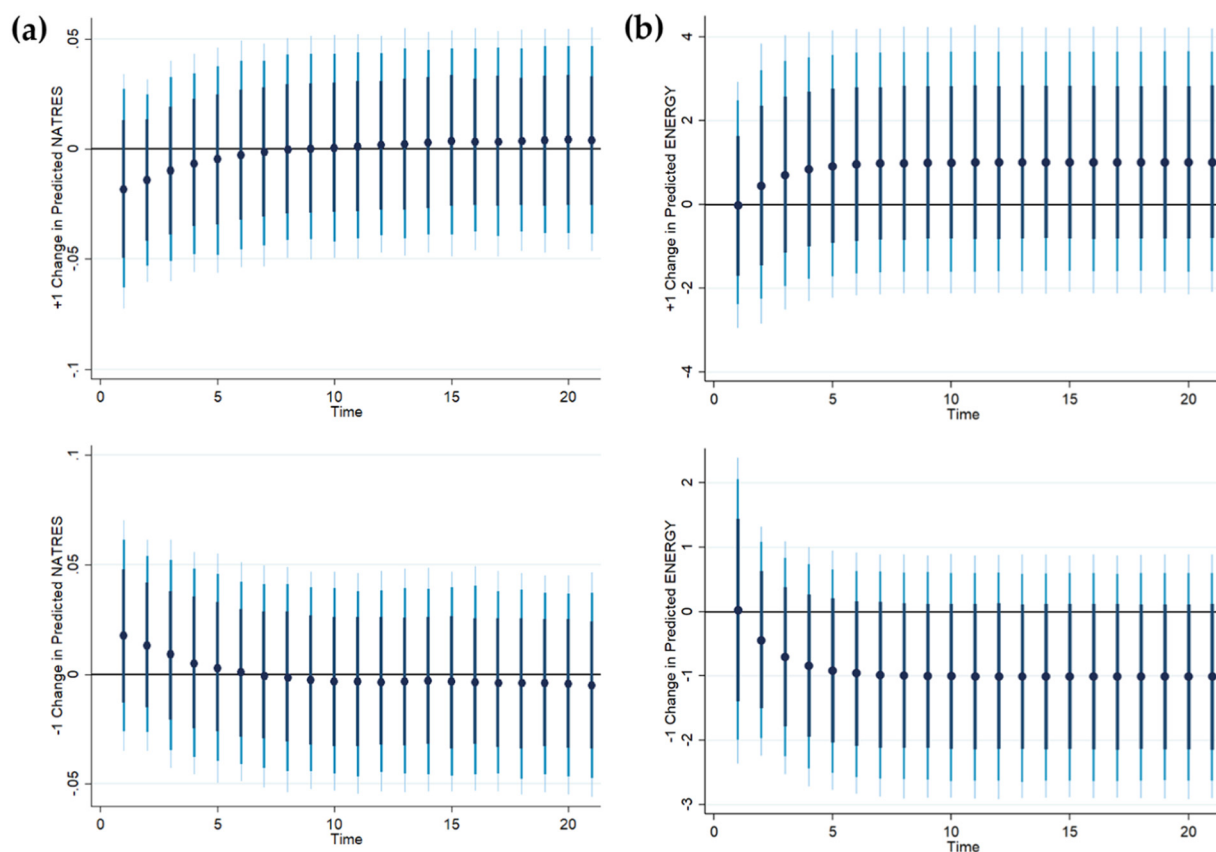

Fig. 2. (a) Model 2: change (±1%) in predicted BIOMAS on GHG (b) Model 2: change in predicted GDP on GHG. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
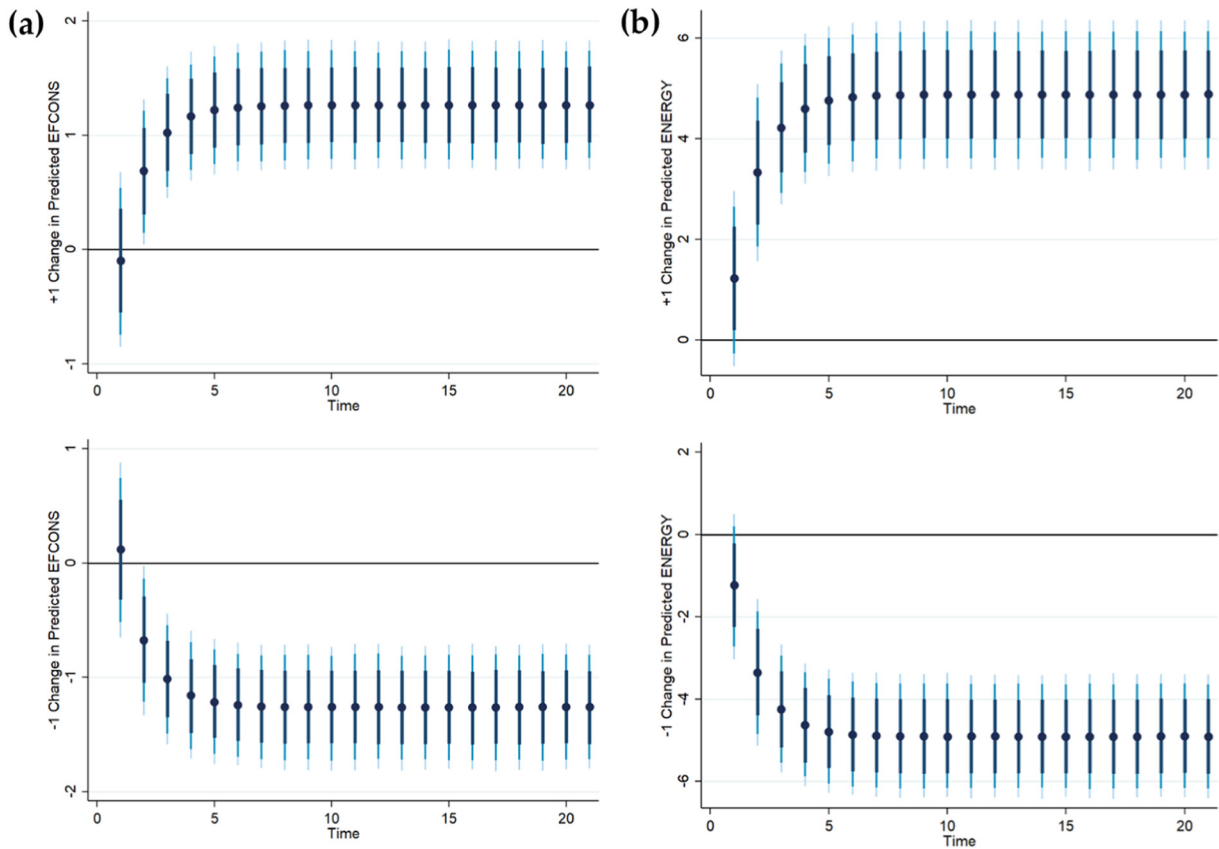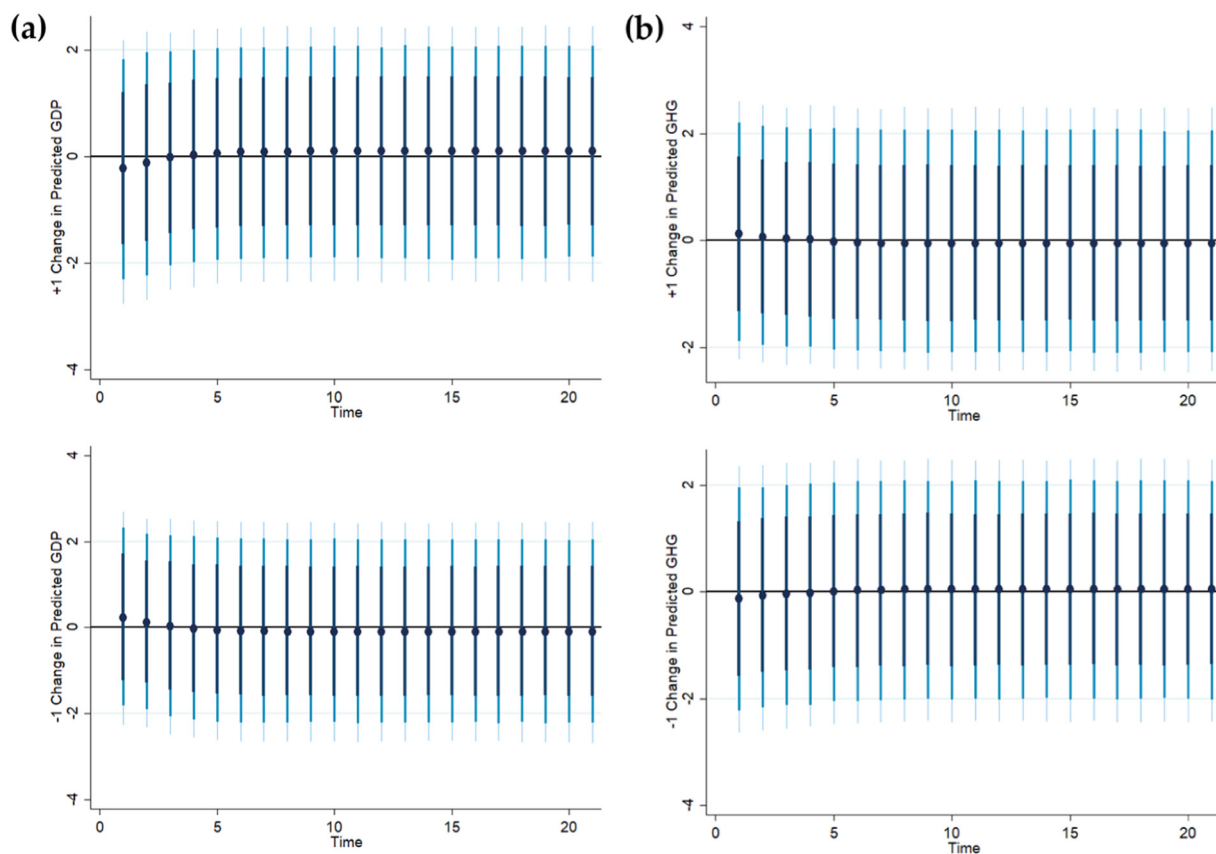
Fig. 3. (a) Model 3: change (±1%) in predicted EFCONS on GHG (b) Model 3: change in predicted ENERGY on GHG. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 4. (a) Model 4: change (±1%) in predicted ENERGY on CO_2E (b) Model 4: change in predicted GDP on CO_2E. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
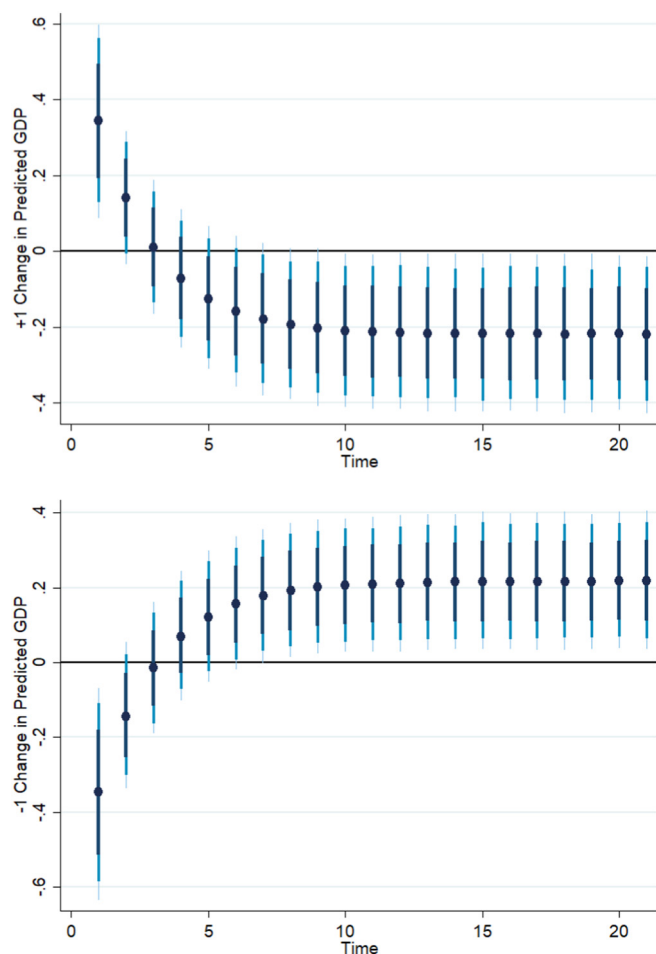
Fig. 5. (a) Model 4: change ($\pm$1%) in predicted NATRES on CO_2E (b) Model 5: change in predicted ENERGY on FOOD. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 6. (a) Model 5: change ($\pm$1%) in predicted GDP on FOOD (b) Model 5: change in predicted GHG on FOOD. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 7. Model 6: Change (±1%) in predicted GDP on EFCONS. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

signs of GHG emissions are evident during mining, processing, smelting and refining of metal ores. Nevertheless, a lifecycle analysis (Norgate and Haque, 2010) on the contribution of mining and mineral processing to GHG emissions revealed that Australia's mining sector performs better in environmental management compared to the global standard. The success story can be attributed to the introduction of "Enduring Value"—Australia's mineral industry framework for sustainable development.

Fig. 2 presents an impulse-response plot of biomass-GHG nexus and economic growth-GHG nexus. Positive or negative shock in biomass extraction and consumption can either negate or affirm GHG emissions benefits. While a positive shock immediately escalates GHG emissions in the short-term, the response stabilizes in the long-term. However, GHG emissions respond immediately to a negative shock in biomass energy consumption but flatten in the long-run. The increasing levels of GHG emissions can be attributed to the non-vanishing life-cycle emissions originating from the use of fossil fuels during pre-planting, planting, regrowth, harvesting and post-harvesting cycles, and potential agricultural, forestry, land-use and management related emissions (Bruckner et al., 2015; Tilman et al., 2009). According to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report, "the direct emissions from biogenic feedstock combustion largely corresponds to the amount of atmospheric CO_2 sequestrated via the growth cycle of bioenergy production" (Bruckner et al., 2015). Other factors affecting biomass lifecycle emissions include inter alia, feedstock type, location, scale

and technologies used in biomass production (Owusu and Asumadu, 2016). For example, the direct use of food crops for energy generation rather than lignocellulosic biomass contributes indirectly to emissions. Both positive and negative future shocks in GDP have relatively no change on GHG emissions, evidenced in Fig. 2(b). The possible explanation may be due to the structural change in economic development, by shifting from carbon-and energy-intensive economy to a decarbonized and services economy, corroborated by Sarkodie and Strezov (2018b); and Sarkodie and Strezov (2018a).

In models 3–4, a positive relationship between GHG/CO_2 emissions and energy consumption was observed, which is consistent with Shahbaz et al. (2017). Australia's reliance on fossil fuel technologies to meet the growing energy demand intensifies GHG emissions rather than negating it. Fig. 3 shows the change in predicted ecological footprint and energy consumption on GHG emissions. A graphical observation reveals a positive response of GHG emissions to a positive shock in both ecological footprint and energy consumption. On the contrary, a negative shock in ecological footprint and energy consumption triggers a negative response in GHG emissions but stabilizes in the long-run. The IPCC 5th Assessment Report revealed electricity and heat production as the major contributors to global anthropogenic GHG emissions. According to Sarkodie and Strezov (2018a), renewable energy sources (wind, solar, hydro, and biomass) contribute only 2% to Australia's energy mix, hence, restructuring of the energy portfolio to increase the share of clean and modern energy technologies is essential to mitigate GHG emissions. The indicator for ecological footprint measures the required biologically productive land and water needed to produce all the resources for consumption and using existing technologies and resource management practices to absorb waste generated (Global Footprint Network, 2017). Hence, ecological footprint, an indicator of environmental degradation, was found to intensify GHG emission in the long-run if overexploited. Limiting the ecological deficit in Australia is required to prevent the liquidation of ecological assets while promoting environmental sustainability.

The impulse-response between energy/economic growth against CO_2 emissions is presented in Fig. 4. A positive shock in energy consumption increases GHG emissions while a negative shock declines GHG emissions. In the same way, a positive shock in economic growth increases GHG emissions after $t = 3$ but reduces anthropogenic GHG emissions in the long-run after $t = 3$. Energy consumption and economic development are essential to achieving sustainable development. However, carbonized and energy-intensive economy due to fossil fuel energy production and utilization result in environmental pressures, depletion of natural resources and creating pollution, hence, increasing GHG emissions. Decoupling economic development from energy consumption and a structural change in the economy, by decarbonization and switching from energy-intensive production to energy-efficient and service economy are pragmatic steps to attaining the 2030 emission targets. Fig. 5(a) reveals that natural resources depletion has a relatively low impact on GHG emissions. Similar studies found a strong positive relationship between natural resources and GHG emissions in 16 European Union countries (Bekun et al., 2019a). A positive shock in natural resources depletion causes a small increase in emissions after $t = 10$ while a negative shock causes a small decline in GHG emissions. Australia is on the verge of achieving a sustainable production and consumption pattern by declining domestic material intensity of the economy and adopting modern technologies needed to produce goods and services. A decline in natural resources depletion is essential to environmental protection and natural resource conservation, thus, achieving environmental sustainability (DiSano, 2002).

3.3.3. Food-energy-economic growth-climate change nexus

In a growing population seeking answers to meet its energy demand, food challenges and economic development, reduction in GHG emissions cannot be ignored. This study adopted food-energy-economic growth-climate change nexus as a conceptual tool to understand the
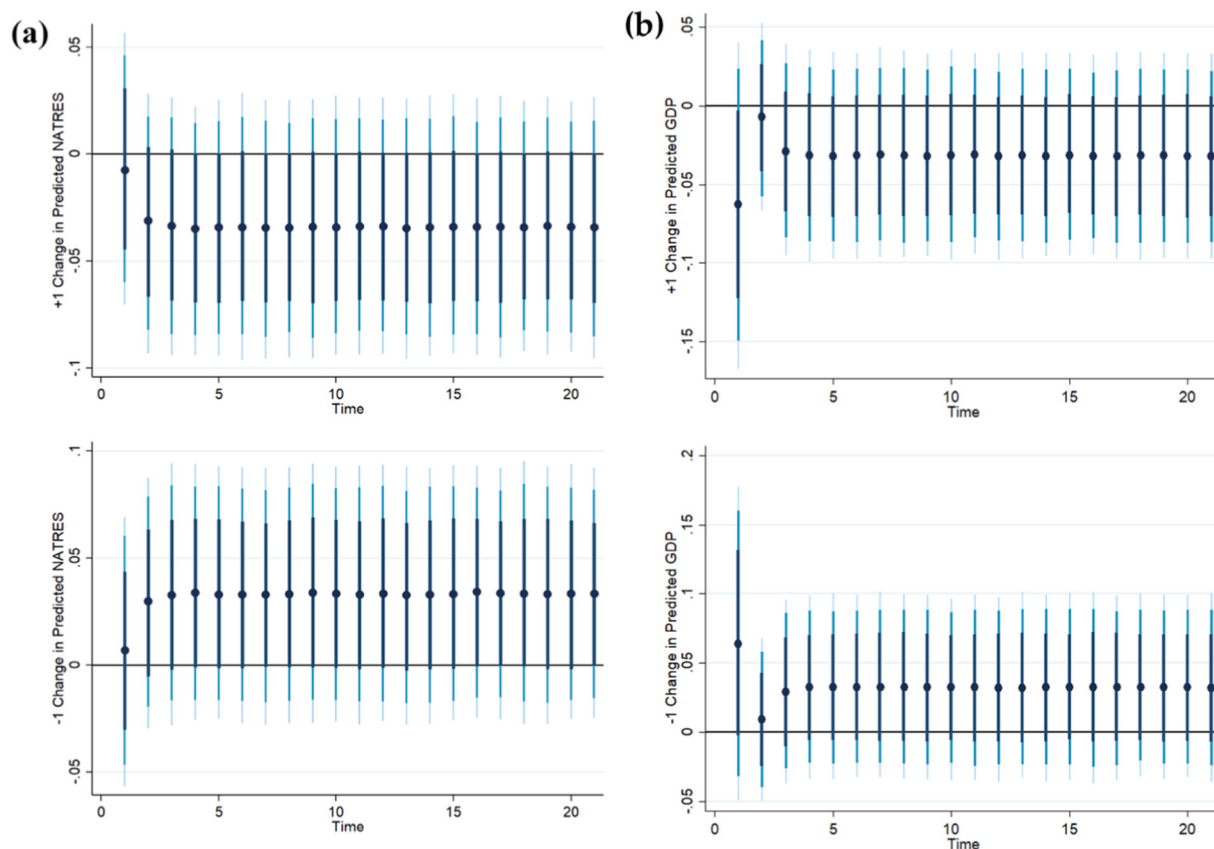
Fig. 8. (a) Model 7: change (±1%) in predicted NATRES on BCAPA (b) Model 7: change in predicted GDP on BCAPA. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

existing dynamics in Australia. Table 5 column 6 reveals a negative and statistically significant error correction of −0.46—representing ~46% speed of adjusting the previous disequilibrium over time as the variables move backwards to a stable long-run relationship. The empirical results show no significant impact of energy/GHG emission on food production in both short- and long-run. On the contrary, economic growth has a negative effect on food production while ecological footprint exhibits a positive impact on food in the short-run. Fig. 5(b) shows that a positive shock in energy increases food after $t = 1$ but the impact stabilizes after $t = 7$. Nevertheless, a negative shock in energy declines food production in the long-run. Energy plays a dominant role in agricultural mechanization used in food production. The role of energy, as a driver of agricultural mechanization improves planting, cultivation, harvesting, food processing and transportation, thus, increases agricultural productivity and ensures a sustainable food security. Fig. 6 depicts the impulse-response between GHG emissions/economic growth versus food production. It is evident in Fig. 6 that a positive shock in economic growth has a relatively low positive impact on food production while a negative shock declines food production. Sustained and inclusive economic growth increases a population's income level and purchasing power, causing an increase in varieties and demand for food, thus, increasing food production. While increasing income level is essential in achieving human development, behavioural changes due to high income trigger the nutritional transition to more affluent food consumption patterns (Gerbens-Leenes et al., 2010), hence, expanding food production at the cost of the natural environment (FAO, 2017). In contrast, Fig. 6(b) shows that a positive shock in GHG emissions declines food production whereas a negative shock adds a little increase to food production. Increasing levels of anthropogenic GHG emissions affect the average global temperature and rainfall patterns, as such,

climate-dependent sectors, such as food production, are vulnerable to climate change impacts.

3.3.4. Ecological footprint-biomass-food-fossil fuel nexus

Table 5 column 7 reveals a 36% speed of adjusting past imbalances to equilibrium following a stable long-run relationship between response and regressors. The nexus between ecological footprint and food production produces a positive effect in both short- and long-run. Population growth has become the main driver of food production in order to meet population demand. However, food choices and consumption patterns have the potential of increasing food production, hence increasing the ecological footprint. For example, a transition from locally available food to imported food products due to affluent lifestyle increases the energy used for pre-harvesting, harvesting and post-harvesting operations. Processed foods utilize a large amount of water, energy and materials for production, packaging, refrigerating, and transportation, in addition to waste generation. Meat production and consumption account for 21% of global carbon footprint, while cereal production and consumption contribute about one-third of food waste, as well as GHG emissions (FAO, 2013; Owusu and Asumadu-Sarkodie, 2017). According to FAO (2013), "one-third of food produced from human utilization is lost or wasted annually, leading to both economic and environmental costs. Food wasted signifies a lost opportunity of improving food security and reduce environmental stress from agricultural production". No significant results were found between ecological footprint, biomass, fossil fuel, metal ore, and non-metallic mineral extraction. However, the role of material consumption and footprint in the capitalization of Australia's economy and environmental sustainability cannot be ignored (United Nations, 2015), perhaps, the

polluting natural resources extracted are exported to developing countries in the form of exports and foreign direct investments (DIIS, 2016).

Fig. 7 presents the impulse-response between economic growth and ecological footprint. A positive shock in economic growth decreases ecological footprint while a negative shock increases ecological footprint in the long-run. Recent studies in Qatar and Industrialized countries revealed a feedback mechanism between economic development and ecological footprint (Charfeddine, 2017; Destek and Sarkodie, 2019) while another study in 27 countries found a unidirectional causality running from economic development to ecological footprint (Uddin et al., 2017). Uddin et al. (2017) accentuated the importance of economic development yet its insufficiency in safeguarding the environment and improving sustainability. Nevertheless, it appears

Australia's economic structure depends more on services and less on natural resource extraction and material consumption, as such, improvements and sustained economic growth reduce ecological footprint, therefore, reducing environmental degradation.

3.3.5. Biocapacity-energy-economic growth-natural resource nexus

The impulse-response between economic growth and natural resources depletion versus biocapacity are presented in Fig. 8. A positive shock in natural resources depletion declines biocapacity while a negative shock improves biocapacity. In addition, a positive shock in economic growth declines biocapacity while a negative shock improves biocapacity in the long-run. The above observations are in accordance with the achievement of environmental sustainability. The exploitation
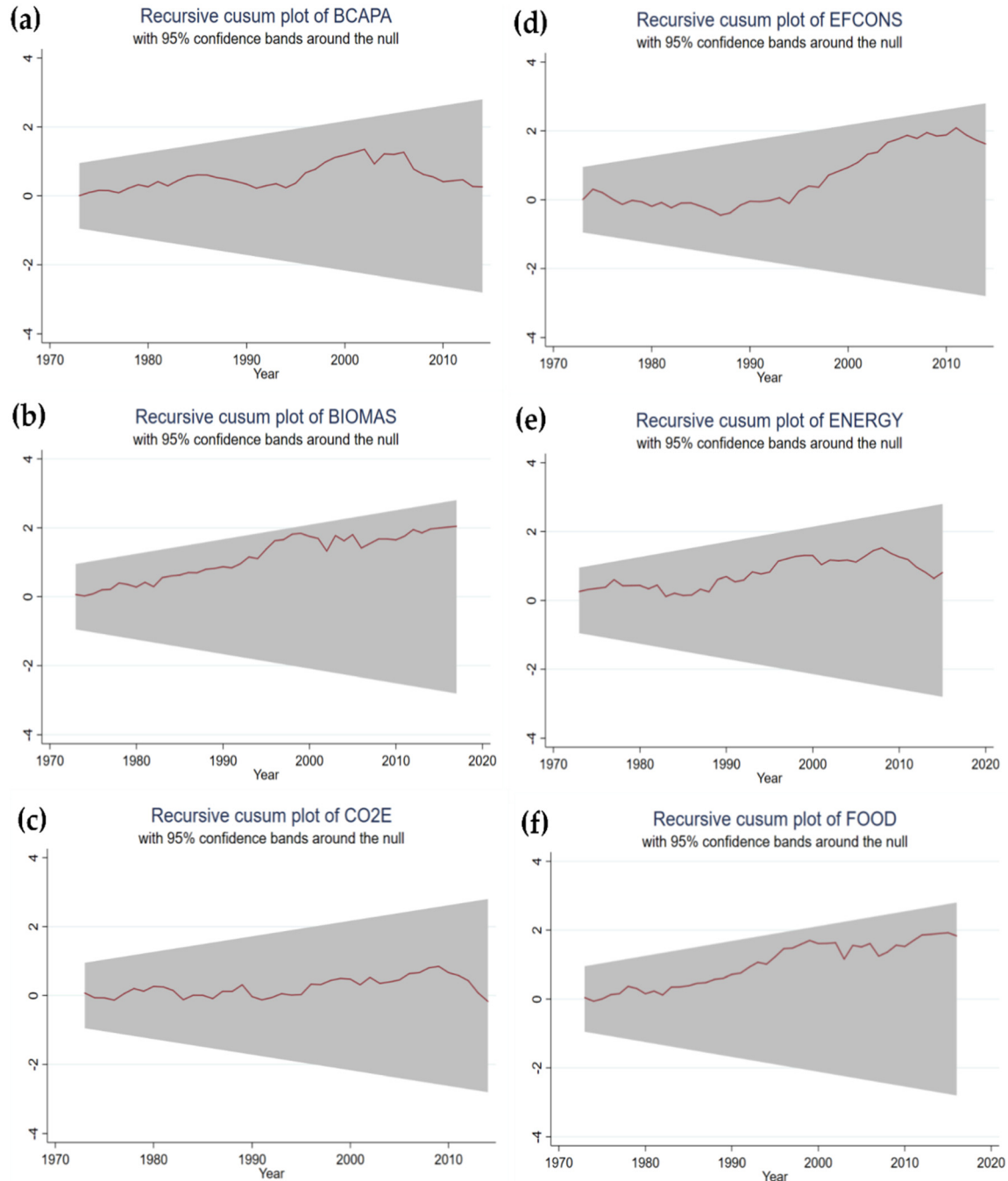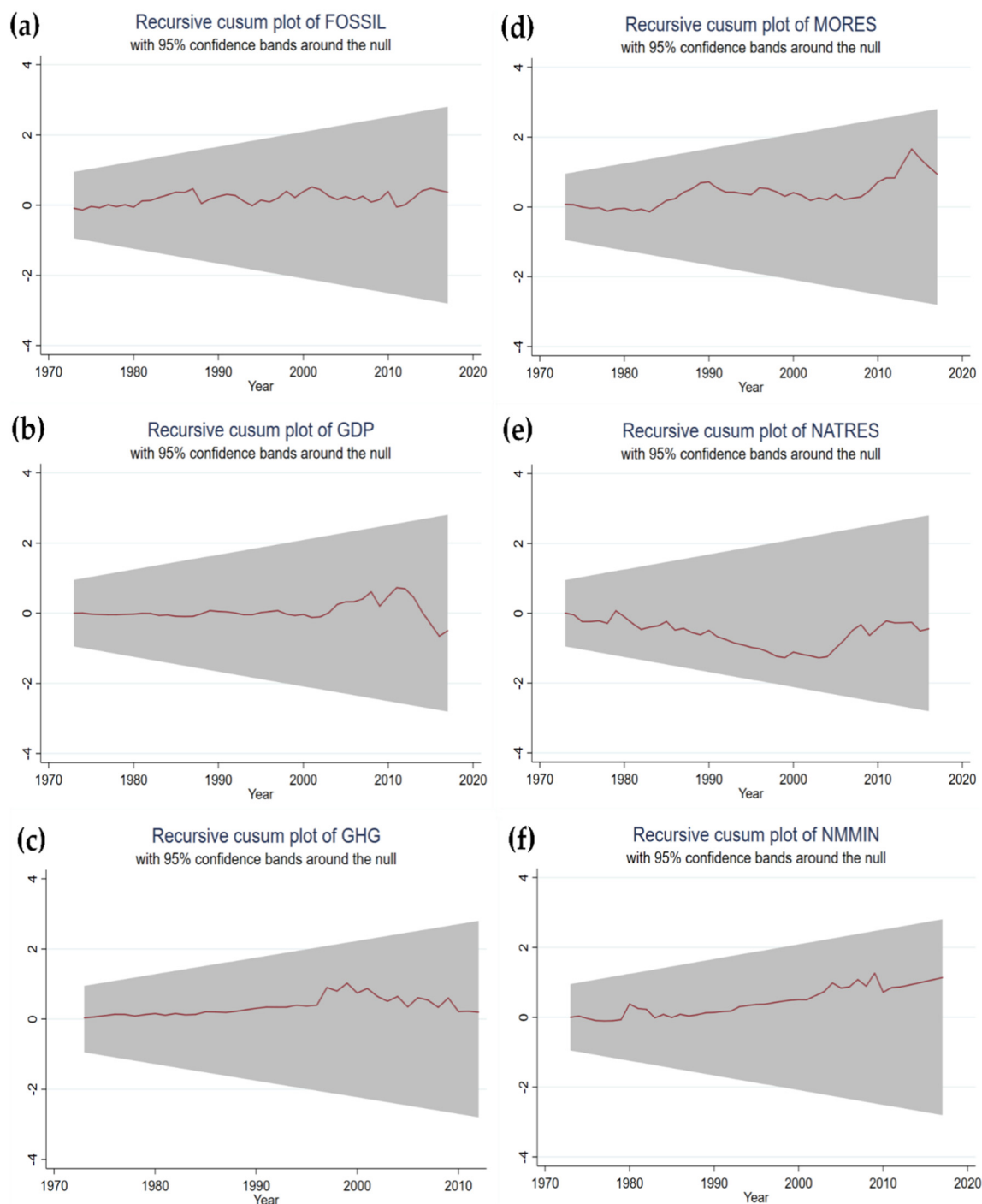

Fig. 9. Recursive cusum plot (a) BCAPA (b) BIOMAS (c) CO_2E (d) EFCONS (e) ENERGY (f) FOOD. NB: The recursive cusum plots within the 95% confidence bands confirm the stability of the estimated models.

of natural resources without sustainable and conservation management practices hampers ecosystems' ability to regenerate itself to support material demand for economic development. Australia's material footprint has increased from 611 million tons in 1996 to 967 million tons in 2015 at a growth rate of 2.74% per annum (UNEP, 2018). The sustainable growth and development entail reduced natural resources depletion, material footprint, the use of toxic materials, and minimizing generated waste and pollutants from cradle-to-grave (United Nations, 2015). Australia's economic growth versus biocapacity negates the theory of environmental sustainability due to the decline of ecosystems' capacity to regenerate itself, hence, leading to an ecological deficit. Corroborated by Sarkodie and Strezov (2018b), the study revealed a

U-shape relationship between biocapacity and economic growth, and a unidirectional causality running from economic development to biocapacity, hence, demonstrating that economic development decreases environmental sustainability in Australia. As a policy implication, decoupling economic development from natural resource extraction and consumption patterns improve environmental sustainability and sustainable development.

3.3.6. Model validation

The estimated models were verified using the diagnostic tests in Table 5 and Figs. 9–10 to examine residual independence. To improve the coefficients and achieve robust standard errors, 5000 dynamic

Fig. 10. Recursive cusum plot (a) FOSSIL (b) GDP (c) GHG (d) MORES (e) NATRES (f) NMMIN. NB: The recursive cusum plots within the 95% confidence bands confirm the stability of the estimated models.

simulations were estimated. The diagnostic tests include Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity; and Breusch-Godfrey LM test for autocorrelation. Results revealed that, except models 3 and 7, the remaining models have no ARCH effect and no issues with autocorrelation. In time-series regression analysis, it is assumed that the coefficients are stable over time. This study applied a CUSUM test to check for structural breaks in the residuals. The work tested the assumption on whether the time series brusquely changes in ways not predicted by the estimated model (Ploberger and Krämer, 1992). The parameter stability of the models is examined using cumulative sum test presented in Figs. 9–10. Evidence from the recursive cusum plot shows that all the data series utilized in the 7 models are within the 95% confidence band, hence, confirming the stability of the estimated models.

4. Conclusion

The complexities of climate change and its impacts require a multifaceted approach to examine the dynamics and interactions with the environment. Using Australia's data as a case study, novel dynamic ARDL simulations were used in this work to examine the interaction between environment and economic policy indicators. Food and energy consumption underpin socio-economic development by improving food security, health and nutrition, income levels, and among others. This study found no significant short and long-run relationship between food and energy consumption. Nevertheless, both positive and shock in food production has a long-term effect on energy consumption. On the contrary, the study found a positive relationship between food and ecological footprint. Food production and its associated services from cradle-to-grave have significant environmental externalities due to the use of energy, natural resources and its related GHG emissions. As such, improvements in sustainable development require sustainable and modern agricultural practices throughout the lifecycle. An inversed-U shaped relationship was found between energy consumption and income level. While growth in income levels intensifies energy consumption, intensive energy utilization declines after reaching a turning point of income level, signifying energy efficiency due to a decline in energy intensity. Australia's energy intensity has declined over the last 30 years due to a structural change in the economy—a paradigm shift from an energy-intensive economy to a decarbonized and services economy, hence, improving energy efficiency. To support the premise, a negative relationship between GHG emissions and economic development is revealed in both short- and long-term, meaning that Australia's economic development is on the pathway to achieving environmental sustainability. Lifecycle emissions of bioenergy sources are problematic in achieving sustainable energy consumption and production patterns. Yet, a negative long-run relationship was observed between GHG emissions and biomass energy consumption. Thus, biomass energy supports a transition to a decarbonized economy by reducing GHG emissions while shifting the demand for fossil fuel energy and its related products. Natural resources depletion was observed to increase ecological footprint as well as increasing GHG emissions. Consequently, limiting Australia's ecological deficit and natural resources exploitation is essential to preventing the liquidation of ecological assets while promoting environmental sustainability.

Policy implications, such as sustainable and conservation management practices for natural resources extraction are required to improve Australia's biocapacity for economic development. Decoupling economic development from natural resource extraction and consumption patterns improve environmental sustainability and sustainable development. Increasing the penetration of renewable energy technologies in the energy mix would reduce energy-related GHG emissions.

An extended discussion on the relationship between food and energy consumption as promoters of socio-economic development with the subsidiary effect of food waste from production and consumption are essential scenarios for the case of the EU. As such, future research

should endeavor to identify the efforts needed to reduce the rate of food waste.

Declaration

There is no conflict of interest.

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